Combining GLCM Features with SVM Classification for Improved Accuracy in Cotton Crop Disease Detection

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***Abstract*— Different diseases affecting cotton plants can be diagnosed and controlled to obtain high yields of good quality cotton. In this study, we propose a methodology for categorizing crop disease images into two groups: diseased and healthy images using feature extraction based on Gray-Level Co-Occurrence Matrix (GLCM) and classification using a Support Vector Machine (SVM). The goal of this study is to improve disease diagnosis using image processing by applying the texture co-occurrence matrix, which gives information on the relationship of pixel intensity of the images. The proposed model is then tested on a cotton crop dataset, and the accuracy score is 86%. These findings enrich the literature by proving the concept that integrating texture-based feature extraction with sophisticated machine-learning approaches to the classification of crop disease highlights diagnostic precision to boost the efficacy of precision agriculture.**

Keywords*— *GLCM, SVM, Cotton crops, disease detection, feature extraction.

I. INTRODUCTION

Cotton is one of the most important crops in the entire world, and unfortunately, it has become vulnerable to numerous diseases which negatively impact the outcome of the harvest. Therefore, early detection and diagnosis should be very crucial in the execution of measures to control these diseases. Even today, conventional approaches to the identification of diseases in this crop plant involving rudimentary surveying and other techniques, along with some initial forms of image analysis, continue to be inadequate and not suitable for extensive farming.

Diagnosis of diseases in crops is very important in order to boost the yield of crops and food security. Farmers should be able to identify the diseases affecting plants at their early stages in order to minimize damage that could lead to poor harvest and added economic loss to the farmers. Pests and diseases can easily infect plants, and there may always be a tendency for farmers to fail to notice the diseases until they become severe. When diseases are detected right from the incubation period, farmers are able to treat the diseases or apply measures to prevent their occurrence, hence greatly lessening the use of pesticides on farms and consequently reducing the impact of these chemicals on the environment. New approaches in image analysis and machine learning provide new strategies for effective and massive-scale disease diagnosis. Such features make the technologies useful in enhancing the ability to bring out detailed diagnoses of images of crops, which, in turn, speeds up the entire process of diagnosing the problem awaiting the crops. The implementation of such automated systems helps to make universally informed decisions. It helps maintain sustainable agriculture practices to increase the strength of the agricultural industry and food security within the community.

Technological advancements, especially in those of machine learning and image processing, have provided new directions in disease detection. Methods that combine feature extraction techniques with classification algorithms are such methods. In particular, the Gray-Level Co-Occurrence Matrix (GLCM) with the Support Vector Machine (SVM) is the most valuable approach for disease detection.

GLCM is a statistical method used in texture analysis in Digital Image Processing that takes into consideration the contextual relationship between pixel intensity. It is rather important to define the differences of symptoms in detail. SVM is another very effective classification technique commonly used in higher-dimension data analysis, and it is very accurate in classifications.

The current review indicates that deep learning is now the most effective method of identifying plant diseases because it learns complicated patterns from large samples of data [1]. It is important to note that due to the huge amount of morphological differences in plants, a variety of imaging methods, which are enhanced by modern algorithms, can greatly enhance the accuracy of disease classification [2]. Furthermore, the approach presented here is the first example of deep learning models being capable not only of identifying plant diseases but also of suggesting further steps and interventions for their treatment, which shows the need for the development of highly effective tools that address specific agricultural requirements [3]. Deep learning has widely been applied in the detection and classification of plant diseases, and it can perform much better than traditional techniques, as evidenced by a systematic review [4]. Following these ideas, this paper is written as a continuation of the identification of a hybrid GLCM-SVM approach, which is designed to improve the reliability and accuracy of detectable diseases in cotton crops through texture-based machine learning classification and feature extraction.

This paper briefly discusses the proposed hybrid GLCM-SVM framework that combines GLCM for feature extraction and SVM classification for disease detection in cotton crops. A hybrid GLCM-SVM approach looks to achieve higher accuracies in detection, which makes it more dependable for farmers and agricultural practitioners.

The major contributions of this paper are as follows:

- To develop an efficient automatic image classification of diseased or healthy bodies with the help of ML SVMs in particular.
- To explore the use of the GLCM in the extraction of features from the cotton disease images.

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- To evaluate the metrics of the SVM classifier on the given GLCM-based features and also to examine how it performs across different image categories.
- To perform statistical tests to compare and differentiate the healthy and diseased sample based on features like dissimilarity, energy, homogeneity, contrast, correlation and Angular Second Moment (ASM) from GLCM.

II. Related Work

Early detection of crop diseases has become much more advanced in the recent past due to the many practices that have been developed to improve on the techniques used. The initial methods focused on improving the visualization of images and their analysis in supervised ways using the help of domain specialists, who were, nonetheless, highly time-consuming and prone to errors. Such conventional approaches were sometimes impracticable in terms of their scale and failure to provide consistent solutions hence the need for new methodologies. Modern developments incorporated image processing and machine learning in the mechanical systems providing more accurate results, and the possibility to analyze a massive amount of information compared to manual monitoring and increasing the general detective effectiveness.

A. Traditional Methods

Traditional methods for the detection of diseases usually require experts who, with field-based sampling supported by laboratory testing, inspect the crops visually. These are reliable methods, but naturally, they are very time- and labor-intensive. Over the past few years, there has been a growing need for an efficient method of detection of diseases that is automated in nature. Khakimov et al. (2022) provide an overview of both traditional and advanced methods for plant disease detection, stressing the importance of early pathogen identification to reduce crop losses [5]. While traditional techniques like visual inspection and microscopy are discussed, the paper also highlights newer methods such as immunodiagnostics and molecular-genetic identification for their enhanced speed and reliability. Rangarajan et al. (2021) explore crop and disease classification using image analysis, comparing the new techniques with traditional approaches [6]. The deep learning model AlexNet demonstrated the highest accuracy.

B. Image Processing Techniques

Using the advanced imaging technology, many researchers have paid attention to image processing techniques for the auto-detection of diseases. These traditional methods mainly employed color features and probably through simple thresholding of images. For instance, a color histogram-based technique was used to detect crops affected by disease, which changes their color. Much of the time, it fails to capture the texture-related features, which go a long way in defining several diseases. Vishnoi et al. (2020) provide elaborate literature on automated plant disease detection systems in India, stating phases like image acquisition, lesion segmentation, and feature extraction, among others, with recommendations for future works [7]. For instance, Iqbal and Talukder (2020) proposed a system to identify early and late blight in potatoes in Bangladesh with 97% accuracy using a random forest classifier based on 450 leaf images [8].

To identify plant diseases, Eunice et al. (2022) sought to use Deep learning models such as DenseNet-121, ResNet-50, and VGG-16, based on the PlantVillage dataset. They further optimized these models, and DenseNet-121 has a remarkable accuracy of 99.81% classification accuracy [9]. To address the issues with complex background and less data, Xiong et al. (2020) developed an Automatic Image Segmentation Algorithm (AISA) using an approach that incorporates the MobileNet CNN model [10]. Their approach enriched the PlantVillage dataset, increasing accuracy and decreasing computational burden. Their mobile system provided more than 80% accuracy in the recognition of 27 diseases of 6 crops, which proclaims the real-world usefulness of such systems.

C. Feature Extraction Techniques

Azim et al. (2021) presented a model for the detection of rice plant diseases such as bacterial leaf blight, brown spot, and leaf smut using feature extraction of color, shape, and texture. Despite their team's comparatively longer time on the platform, their strategy with an extreme gradient boosting decision tree ensemble scored achieve up to 86.58% accuracy in the rice-leaf disease dataset from UCI, surpassing previous models [11].

To mitigate the challenges of visual changes and variations in the environment, Barburiceanu et al. (2021) adapted a feature enhancement framework and DMS-Robust AlexNet, a novel CNN architecture. This single model, which uses multi-scale and dilated convolutional layers, proved to be durable in natural settings and can be utilized for the diagnosis of maize diseases [12]. Altuntaş et al. (2021) achieved 96.99% accuracy in classifying tomato plant diseases and pests from leaf images using deep learning and SVM classifier [13].

D. Classification Techniques

Nandhini et al. (2022) have proposed the Gated-Recurrent Convolutional Neural Network (G-RecConNN) for plantain tree disease detection with CNN and RNN integration for sequential image data with less preprocessing requirement and better real-time accuracy [14]. Goyal et al. (2021) used an improved deep convolutional model for the classification of wheat diseases with an accuracy of 97%. There are high levels of accuracy at 88%, and this is way higher than other known models, VGG16 and RESNET50 [15]. Similarly, Belay et al. (2022) have developed a CNN-LSTM-based model for the diagnosis of chickpea disease in Ethiopia with an overall accuracy of 92.55% showed improved performance as compared to the previous techniques being used [16]. Nikith et al. (2023) compared SVM, KNN, and CNN models with 96% accuracy of the CNN model for the detection of the leaf disease [17]. Such studies affirm the usefulness of deep learning in improving disease identification as well as other assistance in agriculture.

E. Hybrid Approaches

Arshad et al. (2023) proposed the PLDPNet type of a deep hybrid learning model and got a 98.66% accuracy for potato leaf disease prediction through auto-segmentation and deep feature ensemble fusion modules [18]. Sanida et al. (2023) proposed a novel hybrid CNN architecture with an inception module for tomato crop disease identification, which delivers a promising accuracy of 99.17% accuracy [19]. Coffee leaf disease classification using MobileNetV3, Swin Transformer, and variational autoencoder (VAE) has been proposed by Faisal et al. (2023), where the feature fusion model yielded up to 84.29% accuracy indicated an increase in feature extraction [20]. Further, Lamba et al. (2022) proposed the GCL hybrid model, employed LSTM and CNN along with GAN for

dataset enhancement and disease categorization, and achieved 97% accuracy in paddy diseases [21]. These studies prove that integrating different DL approaches and feature merging strategies offers higher disease forecast efficiency and early detection for efficient crop management.

Recent research investigates the incorporation of multiple techniques in search of better accuracy in disease detection. Hybrid approaches coupling feature extraction methods with advanced classification algorithms show potential results. For instance, GLCM combined with SVM has been proposed as a hybrid model for improving classification performance. In such approaches, the strengths of different techniques are used in a complementary manner to realize better results compared to the individual methods.

The paper, thus, goes ahead and proposes the hybrid GLCM-SVM approach for the purpose of integrating the texture analysis capabilities of GLCM with the classification power of SVM to attain improved cotton crop disease detection. A comparative analysis conducted here carries out the effectiveness of such a hybrid approach against traditional SVM methods and points to its potential in practical applications toward precision agriculture.

III. METHODOLOGY

In this study, we developed a machine learning model for classifying medical images into "diseased" and "healthy" categories using an SVM classifier, leveraging texture features derived from the GLCM. The methodology can be divided into several key steps: data preparation, feature extraction, model training and evaluation, and result visualization. Figure 1 illustrates a flow of methodology.

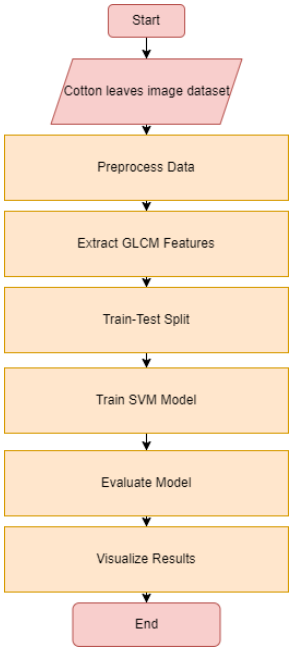

Fig. 1. Methodology flow

A. Data Preparation

The dataset comprises images stored in a specified directory, categorized into two groups: "diseased" and "healthy." The images are first loaded from the respective directories, resized to a uniform dimension of 150x150 pixels, and then organized into arrays of image data and corresponding labels. This ensures consistency in image size and facilitates efficient processing and analysis [22 and 23]. The scaling step adjusts input size to a definite value, which in turn optimizes the feature extraction process. The images were then read, and using a function in OpenCV. These images were converted to NumPy array format for maximum convenience.

B. Feature Extraction

To acquire the textural features of the images, we use GLCM, a statistical method that considers the displacement of the pixel intensities [24]. The feature extraction was carried out using the Gray-Level Co-Occurrence Matrix (GLCM), which was useful in categorizing images into the "diseased" and "healthy" groups. GLCM is one of the methods applied to describe texture by taking into account the spatial relation of pixel intensity in an image. This technique consists of creating a matrix that contains the number of occurrences of pairs of pixels with certain intensity values residing at a fixed spatial relation. In the current study, we concentrated on the following basic GLCM textural features: contrast, correlation, energy, and homogeneity. These features are chosen because they have proved to be useful for detecting the textural characteristics that are required to distinguish the image categories. Keeping these factors in view, the GLCM was extracted with the parameters of pixel distance and angle equal to one and zero, respectively, so that the texture of all the samples was analyzed uniformly. These provided features were then used to train the SVM classifier, which is widely used for image classification.

C. Model Training and Evaluation

In this study, the SVM was trained on features that were derived from images using GLCM, from which textural properties include contrast, correlation, energy, homogeneity, and the ASM. These properties were computed on each image after the images were converted to grayscale so that the model could distinguish between the two categories using only texture. The feature vectors, which are derived from the GLCM of the training images, are used to fit the model. At the end of this phase, the model is assessed on the test set, and subsequent predictions are made [25]. The use of the Radial Basis Function (RBF) kernel is done for their capability to model non-linear mapping from the input features to the target classes. This approach, therefore, confirms the possibility of using GLCM-based feature extraction with SVM when it comes to image-based disease detection tasks.

D. Result Visualization

For the purpose of examining the distribution of the data as well as the performance of the model, several graphs are produced. A Bar plot is drawn to give an insight into the balance of the labels in the dataset. The images of each class are shown to analyze typical "disease visually" and "no disease" images. Hence, histograms of GLCM properties are presented to show the shape of the probability density functions of the texture features for each category. The accuracy of classification is assessed using the decision matrix, specifically the confusion matrix. The bar chart displays the total sample as well as the samples that were correctly classified or recognised for each class. The formula for metrics is as follows:

$$\text{Accuracy} = \frac{\text{Number of correct prediction}}{Total\ prediction} \quad (1)$$

$$\text{Precision} = \frac{\text{Truepositive(TP)}}{\text{TP+falsePositive(FP)}} \quad (2)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FalseNegative(FN)}} \quad (3)$$

$$\text{F1 score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \quad (4)$$

This comprehensive methodology ensures a robust approach to image classification by integrating data preparation, feature extraction, model training, and performance evaluation with effective visualization techniques, providing a clear understanding of the model's capabilities and the characteristics of the dataset.

IV. RESULT

The performance of the image classification model was evaluated through a series of metrics and visualizations to assess its effectiveness in distinguishing between "diseased" and "healthy" categories. The model, trained using an SVM classifier, to classify images based on texture features extracted from the GLCM. Important information on the distribution and properties of the picture dataset, as well as the effectiveness of the classification model, is revealed by the exploratory data analysis (EDA).

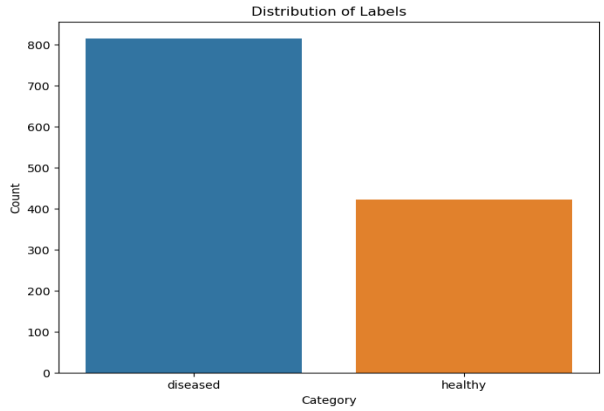

Fig. 2. Class distribution

Fig 2 bar chart shows the distribution of two categories: "diseased" and "healthy." The "diseased" category has a significantly higher count, around 800, compared to the "healthy" category, which has around 450. The chart highlights the imbalance between the two categories in the dataset.

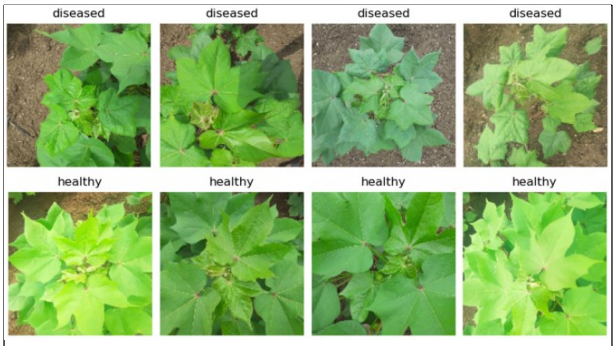

Fig. 3. Sample images from the dataset

Fig 3 shows sample images from a dataset categorized into "diseased" and "healthy" classes. The top row displays various diseased plant leaves characterized by visible damage or discoloration, while the bottom row shows healthy leaves with consistent green coloration. These examples highlight the visual differences crucial for classification tasks.

TABLE I. GLCM PROPERTIES

Property	Diseased (Mean ± Std)	Healthy (Mean ± Std)
Contrast	424.6603 ± 175.5308	287.3720 ± 110.5007
Dissimilarity	12.7299 ± 3.0936	9.5378 ± 2.0559
Homogeneity	0.1472 ± 0.0380	0.2010 ± 0.0336
Energy	0.0172 ± 0.0039	0.0219 ± 0.0043
Correlation	0.8512 ± 0.0568	0.8904 ± 0.0370
ASM	0.0003 ± 0.0002	0.0005 ± 0.0002

Table 1 gives the property of GLCM properties. The exploratory analysis of GLCM properties reveals distinct differences between "diseased" and "healthy" image categories. In contrast, diseased images exhibit higher mean values (424.6603 ± 175.5308) compared to healthy ones (287.3720 ± 110.5007), indicating more texture variability. Diseased images also show greater dissimilarity (12.7299 ± 3.0936) and lower homogeneity (0.1472 ± 0.0380) than healthy images (9.5378 ± 2.0559 and 0.2010 ± 0.0336, respectively), suggesting more texture complexity. Energy is lower in diseased images (0.0172 ± 0.0039) than in healthy ones (0.0219 ± 0.0043), and correlation is slightly lower in diseased images (0.8512 ± 0.0568) compared to healthy ones (0.8904 ± 0.0370). ASM is lower in diseased images,

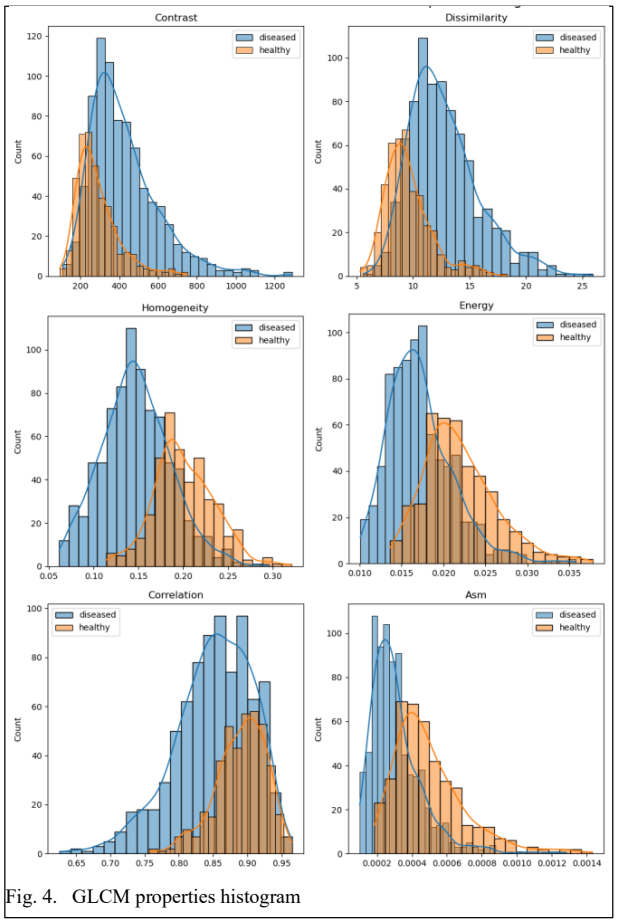

Fig. 4. GLCM properties histogram

reflecting less uniformity in texture. Fig 4 illustrates the GLCM properties histogram.

TABLE II. CLASSIFICATION REPORT

	Precision	Recall	F1-score	Support
0 (Diseased)	0.90	0.89	0.89	167
1 (Healthy)	0.78	0.79	0.79	81
Accuracy			0.86	248
Macro average	0.84	0.84	0.84	248
Weighted average	0.86	0.86	0.86	248

Table 2 offers a breakdown of the assessment of the model. From the table, for class 0 (diseased), the precision value is 0.90. For class 1 (healthy), it is 0.78, recall is 0.79), accuracy is 0.861, with 81 instances. Here, we have witnessed the accuracy of each component, making the total accuracy of the model equal to 0.86, which means 86% of the predictions are correct.

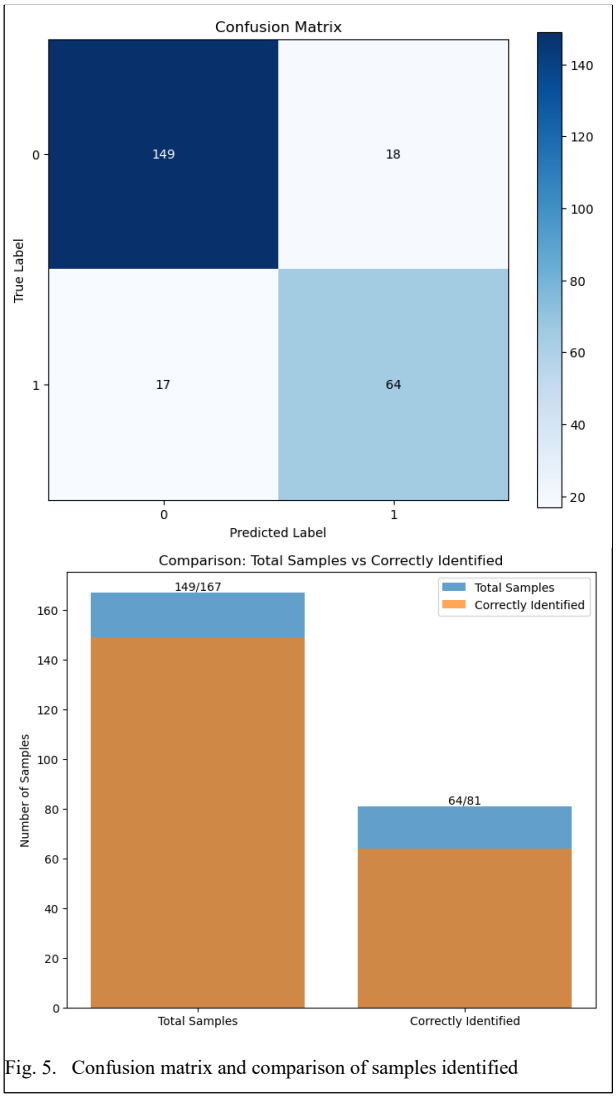

Fig. 5. Confusion matrix and comparison of samples identified

Fig 5 shows a confusion matrix on the left and a bar chart of samples on right. The confusion matrix illustrates the performance of a binary classifier with 167 samples labeled as "0" (negative) and 81 samples labeled as "1" (positive). The classifier correctly predicted 149 negatives and 64 positives. Misclassifications include 18 false positives and 17 false negatives. The bar chart compares total samples with correctly identified samples, emphasizing that most samples were correctly classified, with 149 out of 167 negatives and 64 out of 81 positives accurately predicted. The chart visually contrasts overall performance and accuracy.

Several limitations were observed as the research was being conducted on the developed SVM-based model with high potential of detecting crop diseases: First, due to the use of only GLCM features for extracting the texture features, some detailed patterns and variations might have been lost which is normally seen in diseased and healthy crops. This could restrain the generalizations of the model to other crop types or disease conditions not used in the development of the model. Also important are the options of having a larger and more diverse dataset; such as a large diverse dataset which would make the model more accurate. The images which are passed through the manual resizing process in a way that are predetermined will also lose important information that are important for the model. In addition, the SVM model, which is quite insightful, may not identify the non-linear patterns in the data appropriately as compared to more elaborate models like the deep learning models. Finally, time consumption and calculation for extracting the GLCM features for every image is relatively large which may be a constraint of this research in terms of real time practice in large-scale farming.

V. COMPARATIVE ANALYSIS

TABLE III. COMPARATIVE ANALYSIS TABLE

Paper	Approach	Metric Score
[26]	CNN for crop detection	Accuracy: 80%
[27]	HOG and Random Forest for crop disease detection	Accuracy: 85%
This Paper	GLCM+SVM for crop disease detection	Accuracy: 86%

The establishment of our paper, as demonstrated in Table III, lies in the higher accuracy achieved with the combination of GLCM and SVM for crop disease detection, reaching 86%. This outperforms the CNN approach in [26], which reported an 80% accuracy, and the HOG and Random Forest method in [27], with an accuracy of 85%. Our approach effectively integrates texture-based features from GLCM with the robustness of SVM classification, resulting in more precise detection of crop diseases and highlighting the advantage of hybrid methods in improving classification performance.

VI. CONCLUSION AND FUTURE SCOPE

This study effectively shows how employing feature extraction based on Gray-Level Co-Occurrence Matrix (GLCM) features and employing the Support Vector Machine (SVM) classifier can accurately classify medical images as 'diseased' or 'healthy.' An 86% average accuracy was obtained by the model, proving its capability to classify between the two classes using just the textural features from GLCM. The first basic descriptive statistics of GLCM showed high contrast, dissimilarity, and low homogeneity energy in the diseased images as compared to the healthy ones. These features of texture helped the model to gain useful information that explained why the model was very effective.

Future work could be done in several ways in order to enhance the classification model: Increasing the amount of data gathered to make a larger number of diseased images as well as more healthy images would serve to lessen class imbalance and likely improve results. Moreover, works like deep learning models could be included to enhance the ability

of feature extraction and to increase the rate of true positive results. Adopting other feature extraction techniques apart from GLCM, like LBP or CNN, perhaps can capture more details in the texture and enhance classification outcomes. Therefore, it is suggested that the combination of multiple classifiers or the inclusion of other data be developed in order to have a more practical and realistic scheme of disease diagnosis based solely on images. Such enhancements could mean enhanced diagnostic tools for precision agriculture, which would, in turn, help diagnose crop diseases at their early stages.

The real-life implementation of this approach in farming environments can be achieved by developing a portable, automated system that integrates this method into drones or handheld devices, enabling farmers to capture and analyze crop images in real time for early disease detection. To enhance the results, further research could explore integrating additional features such as hyperspectral or multispectral imaging to capture more detailed crop characteristics. Optimizing the SVM classifier using advanced techniques like hyperparameter tuning or incorporating deep learning models for feature extraction could further improve the detection accuracy. The system could also be connected to smart farming platforms for real-time feedback and decision-making, ensuring faster and more effective crop disease management.

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